

IMPORTING LIBRARIES

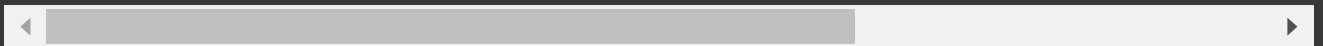
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import os
import sklearn
import tqdm
from tqdm import tqdm
import nltk
import warnings
warnings.filterwarnings("ignore")
import cv2
from sklearn.model_selection import train_test_split
import PIL
from PIL import Image
import time

import tensorflow as tf
import keras
from keras.layers import Input,Dense,Conv2D,concatenate,Dropout,LSTM
from keras import Model
from tensorflow.keras import activations
import warnings
warnings.filterwarnings("ignore")
import nltk.translate.bleu_score as bleu
```

MOUNTING THE DRIVE

```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount('/content/drive', force_remount=True).



```
os.chdir("/content/drive/My Drive/cs2")
```

LOADING CHEXNET MODEL

```
#The trained weights of this model is from https://github.com/brucechou1983/CheXNet-Keras
#https://github.com/antoniosehk/tCheXNet/blob/master/chexnet.py
```

```
from tensorflow.keras.applications import DenseNet121
```

```
image_shape= (224,224,3)
image_input= Input(shape=(224,224,3))
```

```
base=DenseNet121(include_top=False,input_tensor=image_input,input_shape=image_shape)
pred=Dense(14,"sigmoid")(base.output)
```

```
chexnet=Model(inputs=base.input,outputs=pred)
chexnet.load_weights("chexnet_weights.h5")
```

```
chexnet.summary()
```

conv5_block13_concat (Concatenation)	(None, 7, 7, 928)	0	conv5_block12_conv3 conv5_block13_2_conv
conv5_block14_0_bn (Batch Normalization)	(None, 7, 7, 928)	3712	conv5_block13_conv
conv5_block14_0_relu (Activation)	(None, 7, 7, 928)	0	conv5_block14_0_bn
conv5_block14_1_conv (Conv2D)	(None, 7, 7, 128)	118784	conv5_block14_0_relu
conv5_block14_1_bn (Batch Normalization)	(None, 7, 7, 128)	512	conv5_block14_1_conv
conv5_block14_1_relu (Activation)	(None, 7, 7, 128)	0	conv5_block14_1_bn
conv5_block14_2_conv (Conv2D)	(None, 7, 7, 32)	36864	conv5_block14_1_relu
conv5_block14_concat (Concatenation)	(None, 7, 7, 960)	0	conv5_block13_conv conv5_block14_2_conv
conv5_block15_0_bn (Batch Normalization)	(None, 7, 7, 960)	3840	conv5_block14_concat
conv5_block15_0_relu (Activation)	(None, 7, 7, 960)	0	conv5_block15_0_bn
conv5_block15_1_conv (Conv2D)	(None, 7, 7, 128)	122880	conv5_block15_0_relu
conv5_block15_1_bn (Batch Normalization)	(None, 7, 7, 128)	512	conv5_block15_1_conv
conv5_block15_1_relu (Activation)	(None, 7, 7, 128)	0	conv5_block15_1_bn
conv5_block15_2_conv (Conv2D)	(None, 7, 7, 32)	36864	conv5_block15_1_relu
conv5_block15_concat (Concatenation)	(None, 7, 7, 992)	0	conv5_block14_concat conv5_block15_2_conv
conv5_block16_0_bn (Batch Normalization)	(None, 7, 7, 992)	3968	conv5_block15_concat
conv5_block16_0_relu (Activation)	(None, 7, 7, 992)	0	conv5_block16_0_bn
conv5_block16_1_conv (Conv2D)	(None, 7, 7, 128)	126976	conv5_block16_0_relu
conv5_block16_1_bn (Batch Normalization)	(None, 7, 7, 128)	512	conv5_block16_1_conv
conv5_block16_1_relu (Activation)	(None, 7, 7, 128)	0	conv5_block16_1_bn
conv5_block16_2_conv (Conv2D)	(None, 7, 7, 32)	36864	conv5_block16_1_relu
conv5_block16_concat (Concatenation)	(None, 7, 7, 1024)	0	conv5_block15_concat conv5_block16_2_conv
bn (Batch Normalization)	(None, 7, 7, 1024)	4096	conv5_block16_concat
relu (Activation)	(None, 7, 7, 1024)	0	bn[0][0]
dense (Dense)	(None, 7, 7, 14)	14350	relu[0][0]

```
=====
Total params: 7,051,854
Trainable params: 6,968,206
Non-trainable params: 83,648
=====
```

Here we extract the Image features using chexnet model. We use attention mechanism on the image features and give that context vector to the decoder, based on this context vector the decoder generates the word

```
final_chexnet_model=Model(inputs=chexnet.inputs,outputs=chexnet.layers[-2].output,name="Ch
```

LOADING DATA

```
train_dataset = pd.read_csv('Train_Data.csv')
test_dataset = pd.read_csv('Test_Data.csv')
cv_dataset = pd.read_csv('CV_Data.csv')
```

```
train_dataset.head()
```

	Person_id	Image-1	Image-2	Findings
0	x ray data/CXR1_1_IM- 0001_0	x ray data/CXR1_1_IM- 0001-3001.png	x ray data/CXR1_1_IM- 0001-4001.png	SOS the cardiac silhouette and mediastinum siz...
1	x ray data/CXR10_IM- 0002_0	x ray data/CXR10_IM- 0002-1001.png	x ray data/CXR10_IM- 0002-2001.png	SOS the cardiomedial silhouette within no...
	x ray	x ray	x ray	SOS both lungs are clear

```
print(train_dataset.shape)
print(test_dataset.shape)
print(cv_dataset.shape)
```

```
(2758, 4)
(399, 4)
(550, 4)
```

```
#for removing SOS and EOS from findings
def remove(x):
    return x[4:-4]
```

```
train_dataset['Findings'] = train_dataset['Findings'].apply(lambda x : remove(x))
test_dataset['Findings'] = test_dataset['Findings'].apply(lambda x : remove(x))
cv_dataset['Findings'] = cv_dataset['Findings'].apply(lambda x : remove(x))
```

```
train_dataset.head()
```

	Person_id	Image-1	Image-2	Findings
0	x ray data/CXR1_1_IM-0001_0	x ray data/CXR1_1_IM-0001-3001.png	x ray data/CXR1_1_IM-0001-4001.png	the cardiac silhouette and mediastinum size ar...
1	x ray data/CXR10_IM-0002_0	x ray data/CXR10_IM-0002-1001.png	x ray data/CXR10_IM-0002-2001.png	the cardiomedialastinal silhouette within normal...
	x ray	x ray	x ray	both lungs are clear and

```
#finding the number of words in each report
leng=[]
for rep in train_dataset["Findings"]:
    leng.append(len(rep.split()))

print("90th percentile is ",np.percentile(leng,90))
print("99th percentile is ",np.percentile(leng,99))
print("99.9th percentile is ",np.percentile(leng,99.9))
print("Maximum length of report is ",np.max(leng))
```

```
90th percentile is 49.0
99th percentile is 73.0
99.9th percentile is 89.701000000000275
Maximum length of report is 153
```

Here we see that 99.9% of the reports contain less than 100 words even though the maximum words in a report is 155

```
# we obtain the image features from the chexnet model and we predict(7,7,1024) dimensional
#As we have two images for every patient we concatenate them and we perform attention mech
```

```
def image_feature_extraction(image1,image2):
```

```
    image_1 = Image.open(image1)
    image_1= np.asarray(image_1.convert("RGB"))
```

```
    image_2=Image.open(image2)
    image_2 = np.asarray(image_2.convert("RGB"))
```

```
    #normalising the image
    image_1=image_1/255
    image_2=image_2/255
```

```
    #resize the image into (224,224)
    image_1 = cv2.resize(image_1,(224,224))
    image_2 = cv2.resize(image_2,(224,224))
```

```
    image_1= np.expand_dims(image_1, axis=0)
    image_2= np.expand_dims(image_2, axis=0)
```

```
#now we have read two image per patient. this is given to the chexnet model for feature e
```

```

image_1_out=final_chexnet_model(image_1)
image_2_out=final_chexnet_model(image_2)
#concatenate along the width
conc=np.concatenate((image_1_out,image_2_out),axis=2)
#reshape into(no.of images passed, length*breadth, depth)
image_feature=tf.reshape(conc, (conc.shape[0], -1, conc.shape[-1]))

return image_feature

```

```
train_dataset.shape
```

```
(2758, 4)
```

```
cv_dataset.shape
```

```
(550, 4)
```

```
train_features=np.zeros((2758,98,1024))
```

```

for row in tqdm(range(train_dataset.shape[0])):
    image_1=train_dataset.iloc[row]["Image-1"]
    image_2=train_dataset.iloc[row]["Image-2"]
    train_features[row]=(image_feature_extraction(image_1,image_2))

```

```
100%|██████████| 2758/2758 [29:16<00:00, 1.57it/s]
```

```
cv_features=np.zeros((550,98,1024))
```

```

for row in tqdm(range(cv_dataset.shape[0])):
    image_1=cv_dataset.iloc[row]["Image-1"]
    image_2=cv_dataset.iloc[row]["Image-2"]
    cv_features[row]=(image_feature_extraction(image_1,image_2))

```

```
100%|██████████| 550/550 [06:14<00:00, 1.47it/s]
```

```

test_features=np.zeros((399,98,1024))
# test_features=np.zeros((764,98,1024))

```

```

for row in tqdm(range(test_dataset.shape[0])):
    image_1=test_dataset.iloc[row]["Image-1"]
    image_2=test_dataset.iloc[row]["Image-2"]
    test_features[row]=(image_feature_extraction(image_1,image_2))

```

```
100%|██████████| 399/399 [05:55<00:00, 1.12it/s]
```

```

#saving the image features
'''np.save("train_features_attention",train_features)
np.save("test_features_attention",test_features)
np.save("cv_features_attention",cv_features)'''

```

```
#loading the image features
```

```
train_features=np.load("train_features_attention.npy")
test_features=np.load("test_features_attention.npy")
cv_features = np.load("cv_features_attention.npy")
```

```
#checking the shape of features
print(train_features.shape)
print(cv_features.shape)
print(test_features.shape)
```

```
(2758, 98, 1024)
(558, 98, 1024)
(399, 98, 1024)
```

```
#processing the text feature for embedding
train_report=["<sos> "+text+" <eos>" for text in train_dataset["Findings"].values]
test_report=["<sos> "+text+" <eos>" for text in test_dataset['Findings'].values]
cv_report = ["<sos> "+text+" <eos>" for text in cv_dataset['Findings'].values]
```

```
#we are adding sos and eos in front and back of report because it will be useful for decoding
train_report_in=["<sos> "+text for text in train_dataset["Findings"].values]
train_report_out=[text+" <eos>" for text in train_dataset["Findings"].values]
test_report_in=["<sos> "+text for text in test_dataset["Findings"].values]
test_report_out=[text+" <eos>" for text in test_dataset["Findings"].values]
cv_report_in=["<sos> "+text for text in cv_dataset["Findings"].values]
cv_report_out=[text+" <eos>" for text in cv_dataset["Findings"].values]
```

```
print(train_report_in[0])
print(""*100)
print(train_report_out[0])
```

```
<sos> the cardiac silhouette and mediastinum size are within normal limits . there r
*****
the cardiac silhouette and mediastinum size are within normal limits . there no pulm
```

```
#Here we take batch size of 10 and maximum length of report as 100
bs=10
max_len=100
```

```
#Obtaining the text embeddings of the report
# we use the tensorflow tokenizer to convert the text into tokens
#we also pad the sequences to a length 300 which is around the 90th percentile of the length

token=tf.keras.preprocessing.text.Tokenizer(filters='')

token.fit_on_texts(train_report)
vocab_size=len(token.word_index)+1

seq=token.texts_to_sequences(train_report_in)
train_padded_inp=tf.keras.preprocessing.sequence.pad_sequences(seq,maxlen=max_len,padding=
```

```
seq=token.texts_to_sequences(train_report_out)
train_padded_out=tf.keras.preprocessing.sequence.pad_sequences(seq,maxlen=max_len,padding=

seq=token.texts_to_sequences(cv_report_in)
cv_padded_in=tf.keras.preprocessing.sequence.pad_sequences(seq,maxlen=max_len,padding="po

seq=token.texts_to_sequences(cv_report_out)
cv_padded_out=tf.keras.preprocessing.sequence.pad_sequences(seq,maxlen=max_len,padding="po
```

```
print(train_padded_in[98])
```

```
[ 6  2 13 15  8 20 53 46 17  5 19  1  2 14  4 80 16 25 32  1  3  9 12 11
45  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0]
```

```
print(train_padded_out[98])
```

```
[ 2 13 15  8 20 53 46 17  5 19  1  2 14  4 80 16 25 32  1  3  9 12 11 45
 1  7  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
 0  0  0  0]
```

```
len(train_padded_out)
```

```
2758
```

```
#using fast embedding
embeddings_index=dict()
f = open('crawl-300d-2M.vec',encoding="utf8")
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()
print("Done")
# create a weight matrix for words in training docs
```

```
embedding_matrix = np.zeros((vocab_size, 300))
for word, i in tqdm(token.word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
100%|██████████| 1426/1426 [00:00<00:00, 142413.39it/s]Done
```

```
print(token.word_index)
```

```
{'.': 1, 'the': 2, 'no': 3, 'are': 4, 'normal': 5, '<sos>': 6, '<eos>': 7, 'and': 8,
```

```
#checking how many words are there in the embedding file
x = []
for keys in embeddings_index:
    x.append(keys)
print(len(x))
```

```
2000000
```

```
t_w = []
for keys in token.word_index:
    t_w.append(keys)

print(len(t_w))
```

```
1426
```

```
#checking how many common words are present in our vocab and embedding file
t_ws = set (t_w)
x_s = set (x)
com = (x_s & t_ws)
print('{0} % of train words present in embedding file'.format(len(com)/len(t_ws)*100))
```

```
88.218793828892 % of train words present in embedding file
```

MODEL WITH ATTENTION MECHANISM

We extract image features and pass it to the encoder module to give output For decoder we pass the decoder hidden state and encoder output to the attention model which calculate the attention weights Now using the attention weights and encoder output we calculate the context vector

Now we take context vector and embedding vector of decoder input and concatenate it and pass it to gru.

Then gru output is passed to final dense layer

```
enc_units=64
embedding_dim=300
dec_units=64
att_units=64
```

```
input_img=Input(shape=(98,1024),name="image_fetaures")
input_txt=Input(shape=(max_len),name="text_input")

#encoder model
en_out=Dense(enc_units,activation="relu",name="encoder_dense")(input_img)
enc_out=tf.keras.layers.RecurrentWrapper(LSTM(256))(en_out)
```



```
enc_out=tf.keras.layers.Dropout(0.5)(enc_out)

state_h= Input(shape=(bs,enc_units),name="states")
#decoder model with attention

emb_out=tf.keras.layers.Embedding(vocab_size,output_dim=300,input_length=max_len,mask_zero=True)
weights=tf.keras.layers.AdditiveAttention()([state_h,enc_out])
context_vector=tf.matmul(enc_out,weights,transpose_b=True)[:,:,:0]
context_vector=Dense(embedding_dim)(context_vector)
result=tf.concat([tf.expand_dims(context_vector, axis=1),emb_out],axis=1)
gru_out,state=tf.keras.layers.GRU(dec_units,return_sequences=True,return_state=True,name="gru")
out=tf.keras.layers.Dense(vocab_size,name="decoder_final_dense") (gru_out)
en_de=Model(inputs=[input_txt,input_img,state_h],outputs=out)

keras.utils.plot_model(en_de)
```

```

graph TD
    A[image_fetaures: InputLayer] --> B[states: InputLayer]
    A --> C[encoder_dense: Dense]
  
```

states: InputLayer

encoder_dense: Dense

```

#encoder model
#https://www.tensorflow.org/tutorials/text/nmt_with_attention
class Encoder(tf.keras.Model):
    def __init__(self,units):
        super().__init__()
        self.units=units

    def build(self,input_shape):
        self.dense1=Dense(self.units,activation="relu",kernel_initializer=tf.keras.initializer
        self.maxpool=tf.keras.layers.Dropout(0.5)

    def call(self,input_):
        enc_out=self.maxpool(input_)
        enc_out=self.dense1(enc_out)

        return enc_out

    def initialize_states(self,batch_size):
        ...

        Given a batch size it will return intial hidden state
        If batch size is 32- Hidden state shape is [32,units]
        ...

        hidden=tf.zeros((batch_size,self.units))

        return hidden

```

decoder_final_dense: Dense

```

#this is the attention class.
#Here the input to the decoder and the gru hidden state at the pevious time step are given
#This context vector is calculated usng the attention weights. This context vector is the
#Here conact function is used for calaculating the attention weights

```

```

class Attention(tf.keras.layers.Layer):

    def __init__(self,att_units):

        super().__init__()

        self.att_units=att_units

    def build(self,input_shape):
        self.wa=tf.keras.layers.Dense(self.att_units)
        self.wb=tf.keras.layers.Dense(self.att_units)
        self.v=tf.keras.layers.Dense(1)

    def call(self,decoder_hidden_state,encoder_output):

```

```

x=tf.expand_dims(decoder_hidden_state,1)

# print(x.shape)
# print(encoder_output.shape)

alpha_dash=self.v(tf.nn.tanh(self.wa(encoder_output)+self.wb(x)))

alphas=tf.nn.softmax(alpha_dash,1)

# print("en",encoder_output.shape)
# print("al",alphas.shape)

context_vector=tf.matmul(encoder_output,alphas,transpose_a=True)[:,:,:0]
# context_vector = alphas*encoder_output
# print("c",context_vector.shape)

return (context_vector,alphas)

```

#This class will perform the decoder task.
 #The main decoder will call this onestep decoder at every time step. This one step decoder
 #This output is passed through the final softmax layer with output size =vocab size, and p

```

class One_Step_Decoder(tf.keras.Model):
    def __init__(self,vocab_size, embedding_dim, input_length, dec_units ,att_units):

        # Initialize decoder embedding layer, LSTM and any other objects needed
        super().__init__()

        self.att_units=att_units
        self.vocab_size=vocab_size
        self.embedding_dim=embedding_dim
        self.input_length=input_length

        self.dec_units=dec_units
        self.attention=Attention(self.att_units)
    #def build(self,inp_shape):
        self.embedding=tf.keras.layers.Embedding(self.vocab_size,output_dim=self.embedding_dim
                                                input_length=self.input_length,mask_zero=True

        self.gru=tf.keras.layers.GRU(self.dec_units,return_sequences=True,return_state=True,recurrent_initializer='glorot_uniform')
        self.dense=tf.keras.layers.Dense(self.vocab_size,name="decoder_final_dense")
        self.dense_2=tf.keras.layers.Dense(self.embedding_dim,name="decoder_dense2")

    def call(self,input_to_decoder, encoder_output, state_h):

        embed=self.embedding(input_to_decoder)

        context_vector,alpha=self.attention(state_h,encoder_output)

        context_vector=self.dense_2(context_vector)

```

```

result=tf.concat([tf.expand_dims(context_vector, axis=1),embed],axis=-1)

output,decoder_state_1=self.gru(result,initial_state=state_h)
out=tf.reshape(output,(-1,output.shape[-1]))

out=tf.keras.layers.Dropout(0.5)(out)

dense_op=self.dense(out)

return dense_op,decoder_state_1,alpha

```

<https://www.tensorflow.org/tutorials/text/transformer#decoder>

```

class Decoder(tf.keras.Model):
    def __init__(self, vocab_size, embedding_dim, output_length, dec_units,att_units):
        super().__init__()
        #Intialize necessary variables and create an object from the class onestepdecoder
        self.onestep=One_Step_Decoder(vocab_size, embedding_dim, output_length, dec_units,att_units)

    def call(self, input_to_decoder,encoder_output,state_1):

        #Initialize an empty Tensor array, that will store the outputs at each and every time step
        #Create a tensor array as shown in the reference notebook

        #Iterate till the length of the decoder input
        # Call onestepdecoder for each token in decoder_input
        # Store the output in tensorarray
        # Return the tensor array

        all_outputs=tf.TensorArray(tf.float32,input_to_decoder.shape[1],name="output_array")
        for step in range(input_to_decoder.shape[1]):
            output,state_1,alpha=self.onestep(input_to_decoder[:,step:step+1],encoder_output,state_1)

            all_outputs=all_outputs.write(step,output)
        all_outputs=tf.transpose(all_outputs.stack(),[1,0,2])

        return all_outputs

```

```

import warnings
warnings.filterwarnings("ignore")

```

```

class encoder_decoder(tf.keras.Model):
    def __init__(self,enc_units,embedding_dim,vocab_size,output_length,dec_units,att_units,batch_size):
        super().__init__()

        self.batch_size=batch_size
        self.encoder =Encoder(enc_units)
        self.decoder=Decoder(vocab_size,embedding_dim,output_length,dec_units,att_units)

```

```
#Compute the image features using feature extraction model and pass it to the encoder
# This will give encoder output
# Pass the decoder sequence,encoder_output,initial states to Decoder
# return the decoder output
```

```
def call(self, data):
    features,report = data[0], data[1]

    encoder_output= self.encoder(features)
    state_h=self.encoder.initialize_states(self.batch_size)

    output= self.decoder(report, encoder_output,state_h)

    return output
```

```
model = encoder_decoder(enc_units,embedding_dim,vocab_size,max_len,dec_units,att_units,bs)
```

```
optimizer = tf.keras.optimizers.Adam()

loss_function = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True, reduction=

def custom_lossfunction(y_true, y_pred):
    #getting mask value
    mask = tf.math.logical_not(tf.math.equal(y_true, 0))

    #calculating the loss
    loss_ = loss_function(y_true, y_pred)

    #converting mask dtype to loss_ dtype
    mask = tf.cast(mask, dtype=loss_.dtype)

    #applying the mask to loss
    loss_ = loss_*mask

    #getting mean over all the values
    loss_ = tf.reduce_mean(loss_)
    return loss_
```

```
model.compile(optimizer=optimizer,loss=custom_lossfunction)
```

```
red_lr=tf.keras.callbacks.ReduceLROnPlateau(monitor="val_loss",factor=0.2,patience=2, min_
ckpt=tf.keras.callbacks.ModelCheckpoint("model_3/wts",monitor='val_loss', verbose=1, save_
```

```
model.fit([train_features[:2750],train_padded_inp[:2750]],train_padded_out[:2750],validati
        batch_size=bs,epochs=50,callbacks=[red_lr,ckpt])
```

Epoch 1/50

275/275 [=====] - 146s 193ms/step - loss: 1.1181 - val_loss

```
Epoch 00001: val_loss improved from inf to 0.59207, saving model to model_3/wts
Epoch 2/50
275/275 [=====] - 35s 126ms/step - loss: 0.5424 - val_loss: 0.59207

Epoch 00002: val_loss improved from 0.59207 to 0.52921, saving model to model_3/wts
Epoch 3/50
275/275 [=====] - 35s 127ms/step - loss: 0.5146 - val_loss: 0.52921

Epoch 00003: val_loss improved from 0.52921 to 0.46455, saving model to model_3/wts
Epoch 4/50
275/275 [=====] - 34s 124ms/step - loss: 0.4454 - val_loss: 0.46455

Epoch 00004: val_loss improved from 0.46455 to 0.40856, saving model to model_3/wts
Epoch 5/50
275/275 [=====] - 35s 128ms/step - loss: 0.4142 - val_loss: 0.40856

Epoch 00005: val_loss improved from 0.40856 to 0.36613, saving model to model_3/wts
Epoch 6/50
275/275 [=====] - 34s 125ms/step - loss: 0.3773 - val_loss: 0.36613

Epoch 00006: val_loss improved from 0.36613 to 0.33909, saving model to model_3/wts
Epoch 7/50
275/275 [=====] - 35s 126ms/step - loss: 0.3515 - val_loss: 0.33909

Epoch 00007: val_loss improved from 0.33909 to 0.32067, saving model to model_3/wts
Epoch 8/50
275/275 [=====] - 34s 125ms/step - loss: 0.3438 - val_loss: 0.32067

Epoch 00008: val_loss improved from 0.32067 to 0.30528, saving model to model_3/wts
Epoch 9/50
275/275 [=====] - 35s 129ms/step - loss: 0.3222 - val_loss: 0.30528

Epoch 00009: val_loss improved from 0.30528 to 0.29284, saving model to model_3/wts
Epoch 10/50
275/275 [=====] - 35s 126ms/step - loss: 0.3054 - val_loss: 0.29284

Epoch 00010: val_loss improved from 0.29284 to 0.28306, saving model to model_3/wts
Epoch 11/50
275/275 [=====] - 34s 125ms/step - loss: 0.2935 - val_loss: 0.28306

Epoch 00011: val_loss improved from 0.28306 to 0.27520, saving model to model_3/wts
Epoch 12/50
275/275 [=====] - 35s 127ms/step - loss: 0.2860 - val_loss: 0.27520

Epoch 00012: val_loss improved from 0.27520 to 0.26699, saving model to model_3/wts
Epoch 13/50
275/275 [=====] - 34s 125ms/step - loss: 0.2828 - val_loss: 0.26699

Epoch 00013: val_loss improved from 0.26699 to 0.26012, saving model to model_3/wts
Epoch 14/50
275/275 [=====] - 35s 127ms/step - loss: 0.2690 - val_loss: 0.26012

Epoch 00014: val_loss improved from 0.26012 to 0.25368, saving model to model_3/wts
Epoch 15/50
275/275 [=====] - 35s 126ms/step - loss: 0.2616 - val_loss: 0.25368
```

Here I tried with different epochs like 20,30 and 50 as the loss is decreasing and settled with 50 epochs.

```
#loading the weights
model.load_weights("model_2/wts")
```

```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7f97a1d71cf8>
```

```
def take_second(elem):
    return elem[1]
```

TESTING

```
#https://machinelearningmastery.com/beam-search-decoder-natural-language-processing/
def beam_search(image1,image2, beam_index):

    hidden_state = tf.zeros((1, enc_units))

    image_features=image_feature_extraction(image1,image2)

    encoder_out = model.layers[0](image_features)

    start_token = [token.word_index["<sos>"]]
    dec_word = [[start_token, 0.0]]
    while len(dec_word[0][0]) < max_len:
        temp = []
        for word in dec_word:

            predict, hidden_state,alpha = model.layers[1].onestep(tf.expand_dims([word[0]][0],1))

            word_predict = np.argsort(predict[0])[-beam_index:]
            for i in word_predict:

                next_word, probab = word[0][:], word[1]
                next_word.append(i)
                probab += predict[0][i]
                temp.append([next_word, probab.numpy()])
        dec_word = temp
        # Sorting according to the probabilities scores

        dec_word = sorted(dec_word, key=take_second)

        # Getting the top words
        dec_word = dec_word[-beam_index:]

    final = dec_word[-1]

    report =final[0]
    score = final[1]
    temp = []

    for word in report:
```

```

for word in report:
    if word!=0:
        if word != token.word_index['<eos>']:
            temp.append(token.index_word[word])
        else:
            break

rep = ' '.join(e for e in temp)

return rep, score

```

```

#checking on random train points
import random
start=time.time()
#i=random.sample(range(train_dataset.shape[0]),1)[0]
i= 73
img1=train_dataset.iloc[i]["Image-1"]
img2=train_dataset.iloc[i]["Image-2"]
    #show th corresponding x-ray images
i1=cv2.imread(img1)
i2=cv2.imread(img2)
plt.figure(figsize=(10,6))
plt.subplot(131)
plt.title("image1")
plt.imshow(i1)
plt.subplot(132)
plt.title("image2")
plt.imshow(i2)
plt.show()
    #printing the actual and generated results

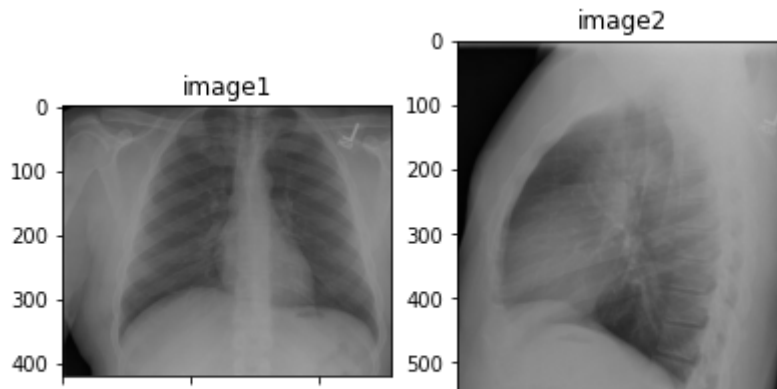
result,score=beam_search(img1,img2,3)
actual=train_report[i]

actual_ref = actual.split()
#actual_ref = [e for e in actual_ref if e not in ('SOS', 'EOS')]
result_ref = result.split()
#result_ref = [e for e in result_ref if e not in ('sos', 'eos')]
#print(actual_ref,result_ref)

print("ACTUAL REPORT: ",actual)
print("GENERATED REPORT: ",result)
end=time.time()
print("BLEU SCORE IS: ",bleu.sentence_bleu(actual_ref,result_ref,weights=(0.25,0.25,0.25,0.25))

print("time required for the evaluation is ",end-start)

```

```
type(result_ref)
```

```
list
```

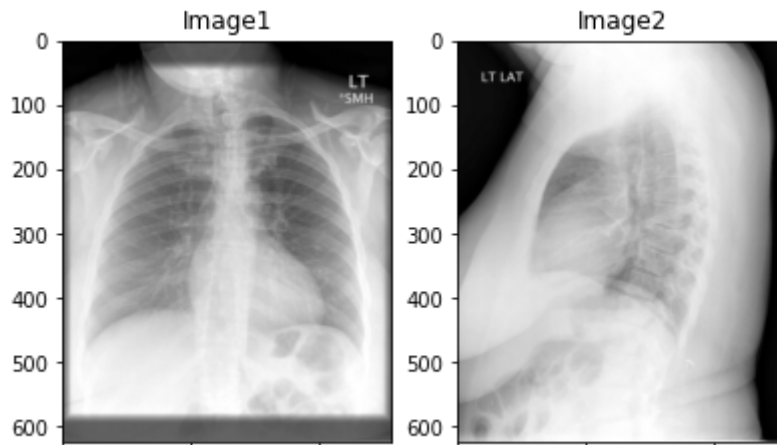
```
GENERATED REPORT: <SOS> the mediastinum . no pleural effusion .
```

```
#checking on random test points
import random
start=time.time()
#i=random.sample(range(test_dataset.shape[0]),1)[0]
i=98
img1=test_dataset.iloc[i]["Image-1"]
img2=test_dataset.iloc[i]["Image-2"]
#show th corresponding x-ray images
i1=cv2.imread(img1)
i2=cv2.imread(img2)
plt.figure(figsize=(10,6))
plt.subplot(131)
plt.title("Image1")
plt.imshow(i1)
plt.subplot(132)
plt.title("Image2")
plt.imshow(i2)
plt.show()
#printing the actual and generated results

result,score=beam_search(img1,img2,3)
actual=test_report[i]
actual_ref = actual.split()
#actual_ref = [e for e in actual_ref if e not in ('SOS', 'EOS')]
result_ref = result.split()
#result_ref = [e for e in result_ref if e not in ('sos', 'eos')]

print("ACTUAL REPORT: ",actual)
print("GENERATED REPORT: ",result)
end=time.time()
print("BLEU SCORE IS: ",bleu.sentence_bleu(actual_ref,result_ref,weights=(0.25,0.25,0.25,0))

print("time required for the evaluation is ",end-start)
```

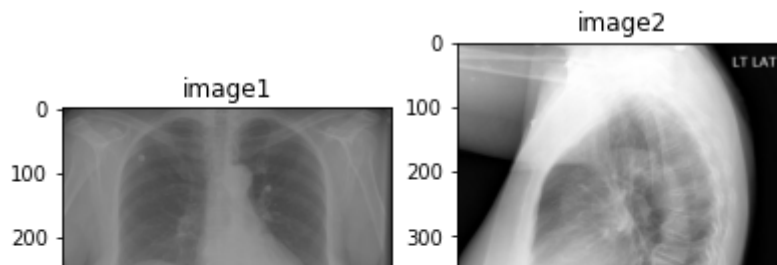


```
#checking on random test points
import random
start=time.time()
#i=random.sample(range(test_dataset.shape[0]),1)[0]
i = 73
img1=test_dataset.iloc[i]["Image-1"]
img2=test_dataset.iloc[i]["Image-2"]
    #show th corresponding x-ray images
i1=cv2.imread(img1)
i2=cv2.imread(img2)
plt.figure(figsize=(10,6))
plt.subplot(131)
plt.title("image1")
plt.imshow(i1)
plt.subplot(132)
plt.title("image2")
plt.imshow(i2)
plt.show()
    #printing the actual and generated results

result,score=beam_search(img1,img2,3)
actual=test_report[i]
actual_ref = actual.split()
gen_ref  = result.split()

print("ACTUAL REPORT: ",actual)
print("GENERATED REPORT: ",result)
end=time.time()
print("BLEU SCORE IS: ",bleu.sentence_bleu(actual_ref,gen_ref,weights=(0.20,0.20,0.20,0.20))

print("time required for the evaluation is ",end-start)
```



```
#checking on random cv points
import random
start=time.time()
i=random.sample(range(cv_dataset.shape[0]),1)[0]
img1=cv_dataset.iloc[i]["Image-1"]
img2=cv_dataset.iloc[i]["Image-2"]
    #show th corresponding x-ray images
i1=cv2.imread(img1)
i2=cv2.imread(img2)
plt.figure(figsize=(10,6))
plt.subplot(131)
plt.title("image1")
plt.imshow(i1)
plt.subplot(132)
plt.title("image2")
plt.imshow(i2)
plt.show()
    #printing the actual and generated results

result,score=beam_search(img1,img2,3)
actual=cv_report[i]
actual_ref = actual.split()
result_ref = result.split()

print("ACTUAL REPORT: ",actual)
print("GENERATED REPORT: ",result)
end=time.time()
print("BLEU SCORE IS: ",bleu.sentence_bleu(actual_ref,result_ref))

print("time required for the evaluation is ",end-start)
```

image2

0

LT LAT

CHECKING ON FULL TEST DATA

```

index=range(0,test_dataset.shape[0])
res=[]
start=time.time()
for i in tqdm(index):
    img_1=test_dataset.iloc[i]["Image-1"]
    img_2=test_dataset.iloc[i]["Image-2"]
    result,score=beam_search(img_1,img_2,3)
    actual=test_report[i]
    actual_ref = actual.split()
    result_ref = result.split()
    res.append(bleu.sentence_bleu(actual_ref,result_ref,weights=(0.25,0.25,0.25,0.25)))
end=time.time()

print("time taken for evaluation is ",end-start)

```

100%|██████████| 399/399 [29:45<00:00, 4.48s/it]time taken for evaluation is 1785.9

```

#checking the maximum bleu score
max(res)

```

0.668740304976422

```
np.mean(res)
```

0.5415717362774637

```
np.median(res)
```

0.5491004867761125

```

#saving in a pickle file
from pickle import dump
dump(res,open('test_res_att_w.pkl','wb'))

```

```

'''#saving in a pickle file
from pickle import dump
dump(res,open('test_res_att.pkl','wb'))

```

```

'''#saving in a pickle file
from pickle import dump
dump(res,open('test_res_att_50.pkl','wb'))

```

PREDICTIONS ON CV DATA

```

index=range(0,cv_dataset.shape[0])
cv_res=[]
start=time.time()
for i in tqdm(index):
    img_1=cv_dataset.iloc[i]["Image-1"]
    img_2=cv_dataset.iloc[i]["Image-2"]
    result,score=beam_search(img_1,img_2,3)
    actual=cv_report[i]
    actual_ref = actual.split()
    result_ref = result.split()
    cv_res.append(bleu.sentence_bleu(actual_ref,result_ref,weights=(0.25,0.25,0.25,0.25)))
end=time.time()
print("time taken for evaluation is ",end-start)

```

100%|██████████| 550/550 [40:22<00:00, 4.40s/it]time taken for evaluation is 2422.4



```
max(cv_res)
```

0.668740304976422

```
min(cv_res)
```

0.33649324423301513

```
np.mean(cv_res)
```

0.5444291127338224

```
np.median(cv_res)
```

0.5557209059832308

```

from pickle import dump
dump(cv_res,open('cv_res_att_w.pkl','wb'))

```

```

'''from pickle import dump
dump(cv_res,open('cv_res_att.pkl','wb'))
'''

```

```

'''from pickle import dump
dump(cv_res,open('cv_res_att_50.pkl','wb'))
'''

```

PREDICTING ON TRAIN DATA

```
index=range(0,train_dataset.shape[0])
```

```

tr_res=[]
start=time.time()
for i in tqdm(index):
    img_1=train_dataset.iloc[i]["Image-1"]
    img_2=train_dataset.iloc[i]["Image-2"]
    result,score=beam_search(img_1,img_2,3)
    actual=train_report[i]
    actual_ref = actual.split()
    result_ref = result.split()
    tr_res.append(bleu.sentence_bleu(actual_ref,result_ref,weights=(0.25,0.25,0.25,0.25)))
end=time.time()
print("time taken for evaluation is ",end-start)

```

100%|██████████| 2758/2758 [3:23:21<00:00, 4.42s/it]time taken for evaluation is 1:



```
max(tr_res)
```

0.668740304976422

```
min(tr_res)
```

0.34449697505113935

```
np.mean(tr_res)
```

0.5444135839012572

```
np.median(tr_res)
```

0.5491004867761125

```

from pickle import dump
dump(tr_res,open('tr_res_att_50_w.pkl','wb'))

```

```

'''from pickle import dump
dump(tr_res,open('tr_res_att_50.pkl','wb'))

```

```

'''from pickle import dump
dump(tr_res,open('tr_res_att.pkl','wb'))

```

PLOTTING ON THE BLEU SCORES OF TRAIN,TEST AND CV DATA

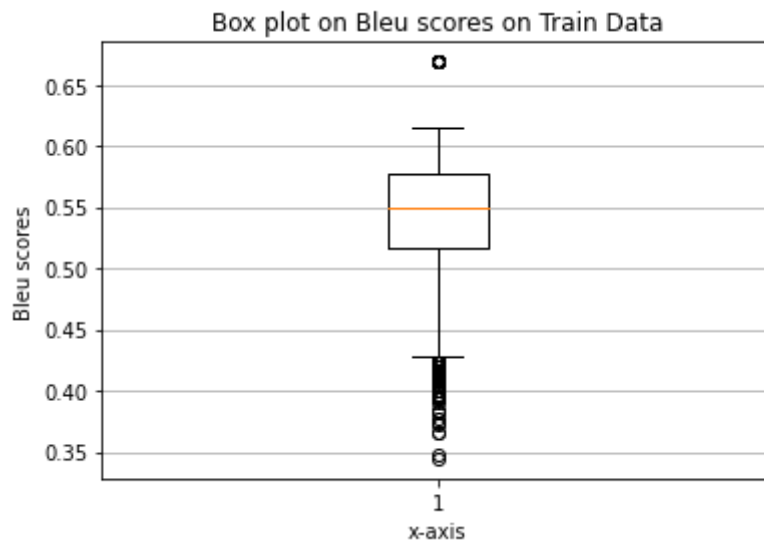
```

#box plot on train predictions
fig, ax = plt.subplots()

data = tr_res
# build a box plot
ax.boxplot(data)

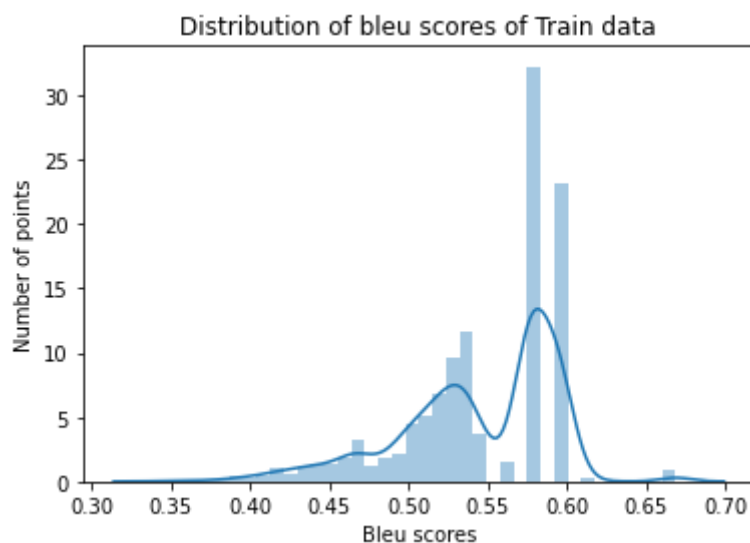
```

```
# title and axis labels
ax.set_title('Box plot on Bleu scores on Train Data')
ax.set_xlabel('x-axis')
ax.set_ylabel('Bleu scores')
ax.yaxis.grid(True)
```



```
#dist plot on train data predictions
pd.set_option('display.max_colwidth', -1)
sns.distplot(tr_res)
```

```
plt.xlabel('Bleu scores')
plt.ylabel('Number of points')
plt.title('Distribution of bleu scores of Train data')
plt.plot()
plt.savefig('bleu_train_gram.png', dpi=600)
```



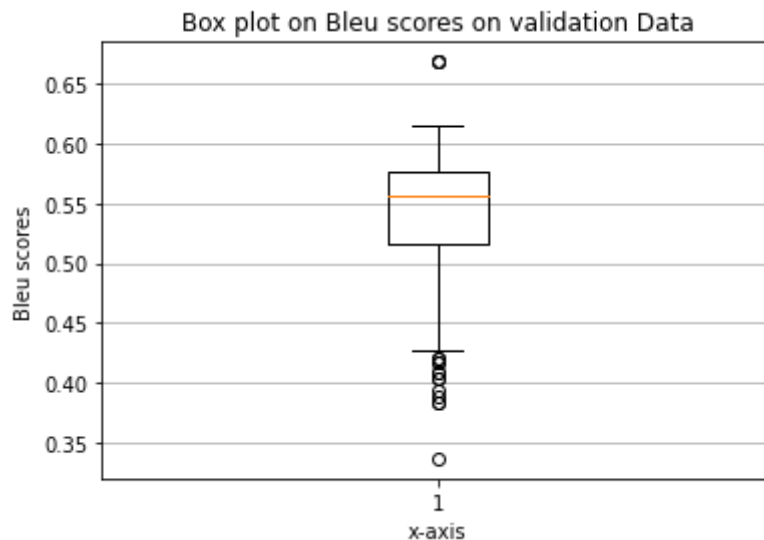
```
#box plot on validation predictions
fig, ax = plt.subplots()
```

```

data = cv_res
# build a box plot
ax.boxplot(data)

# title and axis labels
ax.set_title('Box plot on Bleu scores on validation Data')
ax.set_xlabel('x-axis')
ax.set_ylabel('Bleu scores')
ax.yaxis.grid(True)

```

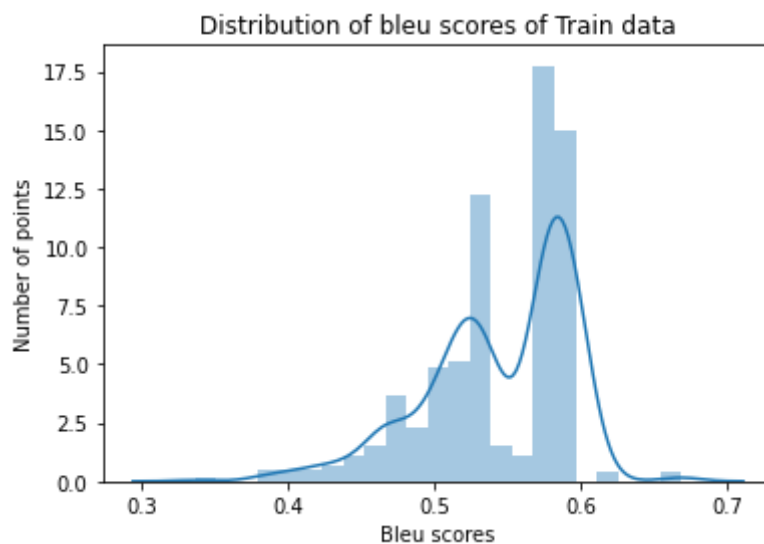


```

#dist plot on cv predictions
pd.set_option('display.max_colwidth', -1)
sns.distplot(cv_res)

plt.xlabel('Bleu scores')
plt.ylabel('Number of points')
plt.title('Distribution of bleu scores of Train data')
plt.plot()
plt.savefig('bleu_validation_gram.png', dpi=600)

```



```

#box plot on test data

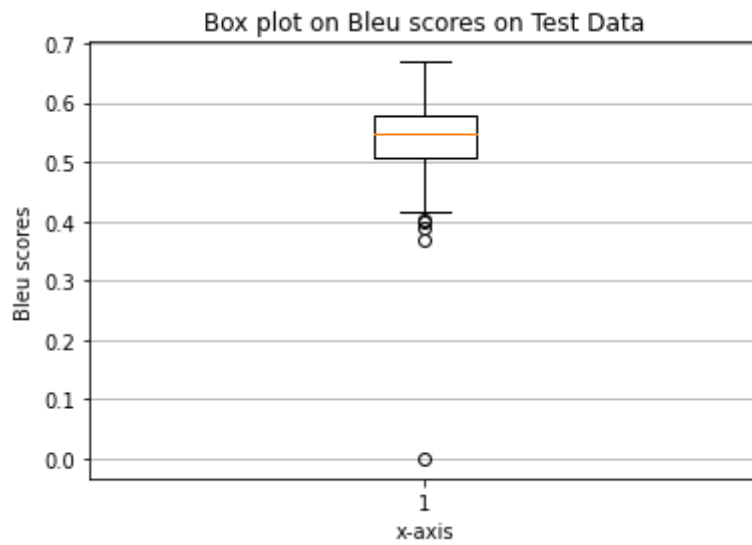
```



```
fig, ax = plt.subplots()

data = res
# build a box plot
ax.boxplot(data)

# title and axis labels
ax.set_title('Box plot on Bleu scores on Test Data')
ax.set_xlabel('x-axis')
ax.set_ylabel('Bleu scores')
ax.yaxis.grid(True)
```



```
#dist plot on test predictions
pd.set_option('display.max_colwidth', -1)
sns.distplot(res)

plt.xlabel('Bleu scores')
plt.ylabel('Number of points')
plt.title('Distribution of bleu scores of Test data')
plt.plot()
plt.savefig('bleu_test_gram.png', dpi=600)
```

Distribution of bleu scores of Test data

FINAL CONCLUSIONS

In this model we got better results compared to first model as we used attention mechanism and beam search for predictions. We can see that median blue score is greater than 0.54 on train, test and validation data. And we got a maximum score of greater than 0.65 on train, test and validation data

Analysing Train Results

```
#loading train results pickle file
import pickle
with open('tr_res_att_50_w.pkl', 'rb') as fp:
    tr_results = pickle.load(fp)
```

```
len(tr_results)
```

```
2758
```

```
min(tr_results),max(tr_results)
```

```
(0.34449697505113935, 0.668740304976422)
```

```
for i in range(1,100,10):
    print('{0} % bleu score is '.format(i),(np.percentile(tr_results,i)))
```

```
1 % bleu score is 0.40546144983876986
11 % bleu score is 0.4728708045015879
21 % bleu score is 0.5081327481546147
31 % bleu score is 0.5266403878479265
41 % bleu score is 0.537284965911771
51 % bleu score is 0.5623413251903491
61 % bleu score is 0.5773502691896257
71 % bleu score is 0.5773502691896257
81 % bleu score is 0.5946035575013605
91 % bleu score is 0.5946035575013605
```

```
#checking for how many points the bleu scores is below 0.5
```

```
wor = 0
better = 0
wor_id = []
#avg_id = []
for i in tr_results:
    if i<0.50:
        wor+=1
        id = tr_results.index(i)
        wor_id.append(id)
    else:
        better+=1
print(wor, better)
```

```
print(wor, better)
```

```
415 2343
```

```
train_dataset['Bleu_scores'] = tr_results
```

```
train_dataset.head()
```

	Person_id	Image-1	Image-2	Findings	Bleu_scores
0	x ray data/CXR1_1_IM-0001_0	x ray data/CXR1_1_IM-0001-3001.png	x ray data/CXR1_1_IM-0001-4001.png	the cardiac silhouette and mediastinum size ar...	0.447214
1	x ray data/CXR10_IM-0002_0	x ray data/CXR10_IM-0002-1001.png	x ray data/CXR10_IM-0002-2001.png	the cardiomediastinal silhouette within normal...	0.451801

```
#dividing the dataset based on bleu scores
wor_df = train_dataset.loc[train_dataset['Bleu_scores'] < 0.50]
print(wor_df.shape)
```

```
(415, 5)
```

```
best_df = train_dataset.loc[train_dataset['Bleu_scores'] >= 0.50]
print(best_df.shape)
```

```
(2343, 5)
```

```
wor_df.head()
```

	Person_id	Image-1	Image-2	Findings	Bleu_scores
0	x ray data/CXR1_1_IM-0001_0	x ray data/CXR1_1_IM-0001-3001.png	x ray data/CXR1_1_IM-0001-4001.png	the cardiac silhouette and mediastinum size ar...	0.447214
1	x ray data/CXR10_IM-0002_0	x ray data/CXR10_IM-0002-1001.png	x ray data/CXR10_IM-0002-2001.png	the cardiomediastinal silhouette within normal...	0.451801

```
#checking the length of report
leng=[]
for rep in wor_df["Findings"]:
    leng.append(len(rep.split()))
for i in range(0,100,10):
    print('{0} % reports length is '.format(i),np.percentile(leng,i))
```

```
0 % reports length is 11.0
10 % reports length is 18.0
20 % reports length is 21.0
```

```

30 % reports length is 25.0
40 % reports length is 28.0
50 % reports length is 30.0
60 % reports length is 33.0
70 % reports length is 37.0
80 % reports length is 41.0
90 % reports length is 49.0

```

```

for i in range(90,100,1):
    print('{0} % reports length is '.format(i),np.percentile(leng,i))

```

```

90 % reports length is 49.0
91 % reports length is 50.0
92 % reports length is 51.0
93 % reports length is 52.020000000000004
94 % reports length is 53.159999999999997
95 % reports length is 55.0
96 % reports length is 59.44
97 % reports length is 63.159999999999997
98 % reports length is 74.439999999999994
99 % reports length is 82.0

```

```
min(leng)
```

```
11
```

```

#findng length of reports in dataframe with bleu >0.5
leng=[]
for rep in best_df["Findings"]:
    leng.append(len(rep.split()))
for i in range(0,100,10):
    print('{0} % reports length is '.format(i),np.percentile(leng,i))

```

```

0 % reports length is 6.0
10 % reports length is 18.0
20 % reports length is 20.400000000000034
30 % reports length is 24.0
40 % reports length is 27.0
50 % reports length is 30.0
60 % reports length is 32.0
70 % reports length is 36.0
80 % reports length is 40.0
90 % reports length is 49.0

```

```

for i in range(90,100,1):
    print('{0} % reports length is '.format(i),np.percentile(leng,i))

```

```

90 % reports length is 49.0
91 % reports length is 50.0
92 % reports length is 51.0
93 % reports length is 52.0
94 % reports length is 54.0
95 % reports length is 56.0
96 % reports length is 57.0
97 % reports length is 60.0

```

```
98 % reports length is 65.0
99 % reports length is 72.0
```

```
min(leng)
```

```
6
```

Here we can see that the length of reports are same almost at all levels

```
#checking images
wor_img_1 = wor_df['Image-1'].unique()
wor_img_2 = wor_df['Image-2'].unique()
```

```
len(wor_img_1),len(wor_img_2)
```

```
(408, 407)
```

```
#finding common images
img_1s = set (wor_img_1)
img_2s = set (wor_img_2)

print(len(img_1s & img_2s))
```

```
57
```

```
bes_img_1 = best_df['Image-1'].unique()
bes_img_2 = best_df['Image-2'].unique()
```

```
len(bes_img_1),len(bes_img_2)
```

```
(2244, 2249)
```

```
img_1s = set (bes_img_1)
img_2s = set (bes_img_2)

print(len(img_1s & img_2s))
```

```
328
```

Here we can see that there are about 57 points out of 400 points which has common images that means these points have only a single image and the same image is used as second image where as in well performed one there will 2 different images which could have impacted the result.

```
#getting words from reports in wor_df
words = []
for rep in wor_df['Findings']:
```

```
x = rep.split()
for i in x:
    words.append(i)
```

```
#getting words from reports in best_df
words_best = []
for rep in best_df['Findings']:
    x = rep.split()
    for i in x:
        words_best.append(i)
```

```
len(words),len(words_best)
```

```
(13655, 73803)
```

```
#converting both words list to sets to find unique words
word_set = set (words)
words_best_s = set (words_best)
```

```
len(word_set),len(words_best_s)
```

```
(729, 1354)
```

```
#checking how many common words are present in the words from wor_df and embedding file
t_ws = set (t_w)#from the embedding file
x_s = set (word_set)
com = (x_s & t_ws)
print('{0} % of train words present in embedding file'.format(len(com)/len(t_ws)*100))
```

```
51.12201963534362 % of train words present in embedding file
```

```
#checking how many common words are present in the words from best_df and embedding file
t_ws = set (t_w)
x_s = set (words_best)
com = (x_s & t_ws)
print('{0} % of train words present in embedding file'.format(len(com)/len(t_ws)*100))
```

```
94.95091164095372 % of train words present in embedding file
```

Here we can see that the only 51% of words which are present in findings of not well performed Dataframe are present in Embedding file

Where as About 96% of words present in findings of well performed dataframe are present in Embedding file.This could have impacted the outcome.

